

NEURAL NETWORK-BASED METAMODELLING
APPROACH FOR ESTIMATION OF AIR POLLUTANT
PROFILES

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NEURAL NETWORK-BASED METAMODELLING APPROACH FOR ESTIMATION OF AIR POLLUTANT PROFILES

By
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CERTIFICATE OF AUTHORSHIP/ ORIGINALITY

I certify that the work in this thesis has not previously been submitted for a similar degree nor has it been submitted as part of requirements for any other degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are referenced in the thesis.

February 2013

A handwritten signature in black ink, appearing to read 'Herman Wahid', written over a horizontal dotted line.

Herman Wahid

This thesis is especially dedicated to my dearest father, mother, wife and family for their love, blessing and encouragement ...

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ABSTRACT

The air quality system is a system characterised by non-linear, complex relationships. Among existing air pollutants, the ozone (O_3), known as a secondary pollutant gas, involves the most complex chemical reactions in its formation, whereby a number of factors can affect its concentration level. To assess the ozone concentration in a region, a measurement method can be implemented, albeit only at certain points in the region. Thus, a more complicated task is to define the spatial distribution of the ozone level across the region, in which the deterministic air quality model is often used by the authority. Nevertheless, simulation by using a deterministic model typically needs high computational requirements due to the nonlinear nature of chemical reactions involved in the model formulation, which is also subject to uncertainties. In the context of ozone as an air pollutant, the determination of the background ozone level (BOL), independent from human activities, is also important as it could represent one of reliable references to human health risk assessment. The concept of BOL may be easily understood, but practically, it is hard to distinguish between natural and anthropogenic effects. Apart from existing approaches to the BOL determination, a new quantisation method is presented in this work, by evaluating the relationship of ozone versus nitric oxide (O_3 -NO) to estimate the BOL value, mainly by using night-time and early morning measurement data collected at the monitoring stations.

In this thesis, to deal with the challenging problem of air pollutant profile estimation, a metamodel approach is suggested to adequately approximate intrinsically non-linear and complex input-output relationships with significantly less computation. The intrinsic characteristics of the underlying physics are not assumed to be known, while the system's input and output behaviours remain essential. A considerable number of metamodels approach have been proposed in the literature, e.g. splines, neural networks, kriging and support vector machine. Here, the radial basis function neural network (RBFNN) is concerned as it is known to offer good estimation performance on accuracy, robustness, versatility, sample size, efficiency, and

simplicity as compared to other stochastic approaches. The development requirements are that the proposed metamodels should be capable of estimating the ozone profiles and its background level temporally and spatially with reasonably good accuracies, subject to satisfying some statistical criteria.

Academic contributions of this thesis include in a number of performance enhancements of the RBFNN algorithms. Generally, three difficulties involved in the network training, selection of radial basis centres, selection of the basis function variance (i.e. spread parameter), and training of network weights. The selection of those parameters is very crucial, as they directly affect the number of hidden neurons used and also the network overall performance. In this research, some improvements of the typical RBFNN algorithm (i.e. orthogonal least squares) are achieved. First, an adaptively-tuned spread parameter and a pruning algorithm to optimise the network's size are proposed. Next, a new approach for training the RBFNN is presented, which involves the forward selection method for selecting the radial basis centres. Also, a method for training the network output weights is developed, including some suggestions for estimation of the best possible values of the network parameters by considering the cross-validation approach. For applications, results show that the combination of the proposed paradigm could offer a sub-optimal solution of metamodeling development in the generic sense (by avoiding the iteration process) for a faster computation, which is essential in air pollutant profile estimation.

PUBLICATIONS

Journal Articles

1. Hiep Duc, Merched Azzi, Herman Wahid, Q.P. Ha, “Background ozone level in the Sydney basin: Assessment and trend analysis”, *Journal of Climatology*, in Press, doi: 10.1002/joc.3595.
2. H. Wahid, Q.P. Ha, H. Duc, “New sampling scheme for neural network-based metamodelling with application to air pollutant estimation,” *Gerontechnology*, vol. 11(2), 2012, pp. 336, doi:10.4017/gt.2012.11.02.325.00.
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Automation and Robotics in Construction (ISARC 2011), Seoul, Korea, 29 Jun-2 Jul 2011, pp. 551-557.

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Related publications

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2. H. Wahid, Q.P. Ha, and M.S. Mohamed Ali, "Optimally-Tuned Cascaded PID Control using Radial Basis Function Neural Network Metamodeling," *Proc. of the 3rd International Workshop on Artificial Intelligence in Science and Technology (AISAT'09)*, Hobart, Australia, 23-24 November 2009, paper S01.2.

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LIST OF ABBREVIATIONS

σ	- RBF spread parameter
σ_c	- Isotropic spread parameter for RBF centres selection
λ	- Regularisation parameter
AQM	- Air quality management
BOL	- Background ozone level
CGS	- Classical Gram-Schmidt
d_2	- Index of agreement
DAQM	- Deterministic air quality model
DOE	- Design of experiments
EPA	- Environment Protection Authority (in Australia)
FFD	- Full factorial design
FS	- Forward selection
GCV	- Generalised cross-validation
GLS	- Generalised least squares
GMR	- Greater Metropolitan Region
LHD	- Latin hypercube design
LOO-CV	- Leave one out cross-validation
LS	- Least squares
<i>MAE</i>	- Mean absolute errors
<i>MSE</i>	- Mean squared errors
NAAQS	- National Ambient Air Quality Standards
NEPM	- National Environment Protection Measures
NO	- Nitric oxide
NO ₂	- Nitrogen dioxide
NO _x	- Nitrogen oxides
O ₃	- Ozone
OLS	- Orthogonal least squares
PM	- Particulate matter
<i>ppb</i>	- parts per billion

<i>pphm</i>	- parts per hundred million
R^2	- Determination coefficient
RBFNN	- Radial basis function neural network
<i>RMSE</i>	- Root mean square errors
<i>SSE</i>	- Sum of squared errors
TEMP	- Ambient temperature
US-EPA	- U.S. Environmental Protection Agency
VOCs	- Volatile organic compounds
WCD	- Weighted clustering design
WDR	- Wind direction
WLS	- Weighted least squares
WSP	- Wind speed